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Spatially explicit modeling of 1992–2100 land cover and forest stand age for the conterminous United States

Terry L. Sohl,[1,6] Kristi L. Sayler,[1] Michelle A. Bouchard,[2] Ryan R. Reker,[2] Aaron M. Friesz,[3] Stacie L. Bennett,[4] Benjamin M. Sleeter,[5] Rachel R. Sleeter,[5] Tamara Wilson,[5] Chris Soulard,[5] Michelle Knuppe,[1] and Travis Van Hofwegen[4]

[1]*U.S. Geological Survey (USGS), Earth Resources Observation and Science (EROS) Center, 47914 252nd Street, Sioux Falls, South Dakota 57198 USA*
[2]*Inuteq, Contractor to USGS EROS Center, 47914 252nd Street, Sioux Falls, South Dakota 57198 USA*
[3]*Information Dynamics, Contractor to USGS EROS Center, 47914 252nd Street, Sioux Falls, South Dakota 57198 USA*
[4]*SGT, Inc., Contractor to USGS EROS Center, 47914 252nd Street, Sioux Falls, South Dakota 57198 USA*
[5]*U.S. Geological Survey, Western Geographic Science Center, 345 Middlefield Road MS 531, Menlo Park, California 94025 USA*

Abstract. Information on future land-use and land-cover (LULC) change is needed to analyze the impact of LULC change on ecological processes. The U.S. Geological Survey has produced spatially explicit, thematically detailed LULC projections for the conterminous United States. Four qualitative and quantitative scenarios of LULC change were developed, with characteristics consistent with the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emission Scenarios (SRES). The four quantified scenarios (A1B, A2, B1, and B2) served as input to the forecasting scenarios of land-use change (FORE-SCE) model. Four spatially explicit data sets consistent with scenario storylines were produced for the conterminous United States, with annual LULC maps from 1992 through 2100. The future projections are characterized by a loss of natural land covers in most scenarios, with corresponding expansion of anthropogenic land uses. Along with the loss of natural land covers, remaining natural land covers experience increased fragmentation under most scenarios, with only the B2 scenario remaining relatively stable in both the proportion of remaining natural land covers and basic fragmentation measures. Forest stand age was also modeled. By 2100, scenarios and ecoregions with heavy forest cutting had relatively lower mean stand ages compared to those with less forest cutting. Stand ages differed substantially between unprotected and protected forest lands, as well as between different forest classes. The modeled data were compared to the National Land Cover Database (NLCD) and other data sources to assess model characteristics. The consistent, spatially explicit, and thematically detailed LULC projections and the associated forest stand-age data layers have been used to analyze LULC impacts on carbon and greenhouse gas fluxes, biodiversity, climate and weather variability, hydrologic change, and other ecological processes.

Key words: FORE-SCE; land cover; land use; model; projection; scenario; United States.

Introduction

Land use and land cover (LULC) in the conterminous United States are expected to change considerably in the coming decades, as demands for food, fiber, energy, and urban development increase. Changes in demographics, government policy, economic conditions, technologic innovation, and climate all have the potential to impact conterminous U.S. LULC (Arnell et al. 2004, Bierwagen et al. 2010, Miguez et al. 2012). Spatially explicit LULC information is important for understanding impacts of landscape change on hydrology (Strayer et al. 2003), climate change (Pielke et al. 1991), biodiversity (Luoto et al. 2007), and carbon fluxes (Zhao et al. 2009). LULC projections are useful for land managers to visualize future landscapes, optimize management practices, and improve planning (Heistermann et al. 2006).

Various LULC modeling frameworks have been developed to investigate potential LULC change for the United States. Radeloff et al. (2012) used an econometric model to spatially model multiple scenarios for the conterminous United States. Wear (2011) used a similar econometric approach to produce county-based projections of land use for three scenarios. Strengers et al. (2004) used an integrated modeling framework to project total global and United States land-use change for multiple scenarios with relatively high thematic detail, but at a coarse spatial resolution. Hurtt et al. (2011) also produced global land-use change for multiple scenarios at a coarse spatial resolution, as well as a coarse thematic resolution. The U.S. Environmental Protection Agency (2005) produced regional projections of major LULC classes in support of an analysis of

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[6] E-mail: sohl@usgs.gov

greenhouse gas mitigation potential. Although each of these efforts provided useful information, each produced projections with trajectories of individual LULC types varying in both magnitude and direction for even similar scenarios. Different model structures, scenario assumptions, thematic classification systems, and spatial characteristics make direct comparison or simultaneous usage of each model's results impractical (Alcamo et al. 2006). Depending upon the modeling framework, the utility of the models for analysis of ecological impacts of LULC change may also be reduced due to (1) the small number of LULC classes modeled, (2) the lack of multiple scenarios (limiting analysis of uncertainty), (3) the coarse spatial scale, and/or (4) the use of a nonspatial modeling framework.

A consistent, spatially explicit, and thematically detailed LULC database such as that produced by the U.S. Geological Survey's (USGS) National Land Cover Database (NLCD) (Vogelmann et al. 2001, Homer et al. 2007) has been used for examining the impacts of LULC on ecological processes across large geographic regions (Beaudry et al. 2010, Zheng et al. 2011, Alam and Goodall 2012). LULC data similar to the level of thematic detail provided by the NLCD, projected forward in time, could be used to analyze the potential effects of LULC change on ecological processes in the future. However, a consistent, high- to moderate-resolution, thematically detailed, and multi-scenario framework is required. National-scale projections with all of these characteristics have been produced for Europe (Verburg et al. 2008), but are not available for the United States. This paper describes the development of spatially explicit projections of future LULC change for the conterminous United States from 1992 through 2100, with projected LULC data of both thematic LULC class, and forested stand age. The projections are then assessed by comparison with multiple data sources. Finally, a discussion of the projections describes their strengths and weaknesses and provides suggestions for their potential use.

Background

The Energy Independence and Security Act (EISA) passed by the U.S. Congress in 2007 mandated the U.S. Department of the Interior to conduct an assessment of carbon storage, carbon sequestration, and greenhouse gas (GHG) fluxes for ecosystems of the United States. To satisfy the requirements of the EISA, the USGS initiated the Biological Carbon Sequestration Project (Zhu et al. 2010). One component of work was the analysis of future potential landscapes of the United States, information that ultimately would be integrated with models of fire, and both terrestrial and aquatic modeling of the resultant GHG impacts.

Required LULC projection characteristics needed to support this work included (1) spatially explicit LULC maps at moderate to high resolution, (2) adequate thematic detail to facilitate the analysis of GHG fluxes, (3) information on forest structure, to facilitate analyses of GHG fluxes due to forest change, and (4) scenario-based projections to allow for an examination of multiple potential futures.

We have developed a methodology to produce spatially explicit, thematically detailed, scenario-based LULC projections for the conterminous United States. The modeling framework also includes the tracking and modeling of forest stand age.

Methods

The primary goal of this work was to produce annual LULC data for the conterminous United States for the years 1992–2100, at a spatial resolution of 250 m. 1992–2005 served as the baseline period, while 2006–2100 represented the projected period. The baseline period represented a time when wall-to-wall LULC data from NLCD were available for multiple dates (1992, 2001,

TABLE 1. Modeled land-use and land-cover (LULC) classes, original 1992 data source, modeled 1992–2005 change (historical period), and modeled 2005–2100 change (projection period); all values are in km^2.

					2005–2100 change, by scenario			
1992 Source	Class	1992	2005	1992–2005 Change	A1B	A2	B1	B2
NLCD	water	227 772	230 002	+2 230	+22	−1 359	+4 478	+11 308
NLCD	urban	171 832	204 622	+32 790	+264 976	+331 243	+163 970	+76 429
VCT	clearcut (NF)	11 662	5 186	−6 476	+11 150	+3 028	+1 571	+5 675
VCT	clearcut (OP)	4 790	4 176	−614	+3 016	+237	−1 405	+350
VCT	clearcut (PV)	53 434	54 717	+1 283	+44 208	−4 028	−7 346	+19 998
NLCD	mining	6 658	9 279	+2 621	+7 231	+9 415	−889	+3 464
NLCD	barren	110 347	110 850	+503	+31	+22	−404	−1 204
NLCD	deciduous	917 339	920 294	+2 955	−196 113	−376 838	−31 039	+48 053
NLCD	evergreen	1 010 707	1 004 967	−5 740	−105 926	−158 306	−2 348	+23 834
NLCD	mixed	334 882	334 318	−564	−68 421	−123 611	−7 942	+10 959
NLCD	grassland	1 240 123	1 243 781	+3 657	−366 928	−414 448	−181 892	+7 467
NLCD	shrubland	1 415 279	1 412 692	−2 586	−135 447	−151 495	−69 525	+7 476
NLCD	cropland	1 339 133	1 323 218	−15 915	+378 144	+673 809	+130 220	−178 970
NLCD	hay/pasture	723 072	709 541	−13 532	+192 547	+261 400	−19 841	−80 022
NLCD	herbaceous wetland	98 352	98 458	+106	−14 878	−23 397	+9 496	+21 811
NLCD	woody wetland	214 219	213 617	−602	−13 613	−25 672	+12 896	+23 381

Notes: The urban class is an aggregation of 1992 national land cover database (NLCD) low-intensity residential, high-intensity residential, commercial/industrial/transportation, and urban/recreational grasses classes. In the three clear-cut classes, vegetation change tracker (VCT) data were used to establish initial 1992 values, and the protected areas data set for the USA (PAD-US) database was used to spatially partition by ownership class; national forest (NF), other public land (OP), and private land (PV). The cropland class is an aggregation of 1992 NLCD row crops, small grains, fallow, and orchards/vineyards/other classes.

U.S. Environmental Protection Agency (EPA) ecoregions (Omernik 1987). LULC modeling was conducted individually for each of the 84 Level III ecoregions as mapped by the 1999 ecoregion publication (U.S. EPA 1999). The forecasting scenarios of land-use change (FORE-SCE) model was used for spatial modeling (Sohl et al. 2007, 2012*a*, *b*). Alcamo et al. (2006) found that local patterns of LULC change are typically determined by biophysical site information, while forces driving overall proportions of change come from larger-scale, outside drivers such as global trade or demographic change. To account for both bottom-up and top-down drivers of change, FORE-SCE uses a modular approach as originally developed by the conversion of land use and its effects (CLUE) series of LULC models (Verburg et al. 1999, 2008). A nonspatial "demand" component produces future proportions of LULC change at an aggregated regional level. Downscaled, quantitative, and qualitative scenarios for each of the 84 ecoregions serve as demand for this work. The spatial allocation component of FORE-SCE ingests demand and produces spatially explicit LULC maps. Fig. 1 provides a schematic of the basic project structure, including the major data components.

Demand and scenarios

The demand component of the modeling framework is provided by (1) historical LULC proportions for the baseline 1992–2005 period, and (2) future scenarios for the 2006–2100 projection period. Demand consists of proportions of LULC at the aggregate regional level, with the 84 Level III ecoregions of the conterminous United States serving as our regional framework. For the baseline 1992–2005 period, proportions of historical LULC data on an annual basis were provided by (1) USGS land-cover trends data (Loveland et al. 2002) for the 1992–2000 period, and (2) annualized LULC change data from the 2001 and 2006 NLCD (Xian et al. 2009) for the 2001–2005 period.

This assessment used a story-and-simulation approach for future scenario development (Alcamo 2008), with qualitative storylines expressed by quantified LULC proportions for each scenario. The scenario framework was based on the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES; see Nakicenovic et al. [2000] for detailed scenario characteristics). Four scenarios were modeled: A1B, A2, B1, and B2. A considerable challenge was downscaling land-use assumptions of the global-scale IPCC SRES to a suitable scale for this assessment. Past IPCC analyses have used integrated modeling frameworks to examine linkages and feedbacks between biophysical and socioeconomic processes that drive climate change. For analyses of SRES, the integrated model to assess the global environment (IMAGE) (Strengers et al. 2004) was the framework that had the most detailed treatment of land use. While IMAGE LULC data were thematically detailed enough to support this work, they were only available for very coarse spatial resolutions (0.5° grid cell). In addition, as a global model, regional results were questionable within the United States, with general trends in LULC classes deemed to be reasonable and consistent with SRES scenario characteristics, but with magnitudes of change that were often unrealistic.

In lieu of directly using IMAGE data as demand, a medley of data sources were used. IMAGE data, other

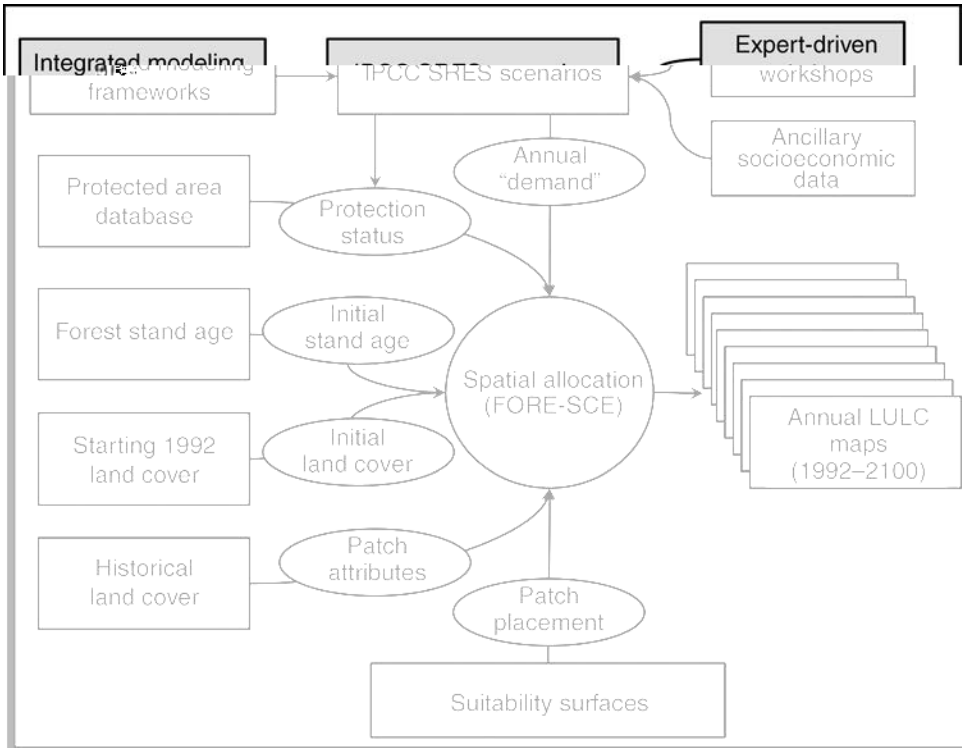

FIG. 1. Schematic of general modeling design. Scenarios based on the Intergovernmental Panel on Climate Change Special Report on Emission Scenarios (IPCC SRES) assumptions provide "demand" (land-use and land-cover [LULC] proportions). The scenarios and protected areas data set for the USA (PAD-US) determine the status of protected lands. The forest stand-age and 1992 National Land Cover Database (NLCD) images set initial landscape conditions. U.S. Geological Survey (USGS) trends data determine the patch attributes for each LULC class. The suitability surfaces prioritize where change patches are placed on the landscape. The spatial allocation component of the forecasting scenarios of land-use change model (FORE-SCE) ingests these data and parameters and produces annual LULC maps.

projected LULC data, ancillary socioeconomic data, and historical databases of LULC were used in a workshop setting by regional LULC experts to create hierarchically downscaled, qualitative, and quantitative scenarios of LULC change consistent with SRES assumptions. A priority was to maintain the storylines provided by the scenarios and by the IMAGE data themselves, but restrain LULC change to realistic proportions. For example, IMAGE called for agricultural land to almost double in area in the United States by 2100 for the A2 scenario, with a 50% projected increase for A1B. Extensive map books of historical land use, socioeconomic, climate, and other spatial data were created for the scenario workshops, including maps of historical agricultural land extent and crop capability indices (biophysical capability of a parcel of land to support cropland). In the workshop, experts in United States land use examined the IMAGE projections and compared them to other projections, to historical data, and to data such as the crop capability index. The quantity of agricultural land called for within the IMAGE-based A1B and A2 scenarios would far surpass any historical extent of agricultural land use; Zumkehr and Campbell (2013) note ~680 000 km^2 of abandoned cropland from the peak cropland extent in the United States to present, while IMAGE called for nearly 3 million km^2 of new cropland between 2000 and 2100 in the A2 scenario. Allocation of that much new cropland would necessarily require using extremely marginal lands for agriculture. Thus, workshop participants decided to maintain the storyline of very strong agricultural land increases in the A1B and A2 scenarios, but temper the quantities to more reasonable levels, based on historical agriculture extent and the amount of land available in the various categories of crop capability.

Both qualitative storylines and quantitative future proportions of LULC change were initially constructed at the national scale, and iteratively downscaled within the workshops to Level I, Level II, and finally Level III ecoregions. The net results were quantitative proportions of future LULC at 5-yr increments from 2005 to 2100 for each of the four SRES storylines, for each of the 84 Level III ecoregions. A much more comprehensive discussion of the preliminary scenario construction process can be found in Sleeter et al. (2012).

Spatial modeling

Modeling methodology.—The FORE-SCE model uses quantitative proportions of LULC from the downscaled scenarios and produces annual, spatially explicit maps. FORE-SCE uses a patch-based modeling approach, placing individual patches of new LULC on the landscape until demand for a scenario is met for a given year. The specification of scenario-based demand and all FORE-SCE model parameterization described was done independently for each of the 84 ecoregions. Characteristics of new LULC patches were determined from historical LULC characteristics within each ecoregion, as measured by the USGS land cover trends and NLCD projects, with projected patch sizes typically mimicking historical patch size distributions. Patch size distributions could also be altered to fit defined LULC characteristics for a given scenario.

The placement of patches of LULC changes was dictated by suitability surfaces that were produced by examining empirical relationships between the existing LULC class and spatially explicit ancillary data, using a logistic regression approach. With 84 ecoregions and approximately 16 LULC classes present in most ecoregions, over 1300 individual suitability surfaces were produced for the conterminous United States. The modified 1992 NLCD served as the dependent variable, while independent variables included a wide variety of spatial data, such as climate, soils, topography, and socioeconomic variables (for a list of typical independent variables, see Sohl et al. 2012*b*). For each LULC class and ecoregion, between 500 and 1500 (if available) randomly distributed points were selected from the modified 1992 NLCD, and LULC class and corresponding ancillary data values were extracted. An initial stepwise logistic regression was run that included all ancillary data sets. To ensure explanation by causation, rather than just statistical correlation, independent variables selected by the initial stepwise regression were examined for likely relevance in explaining suitability of the land to support a given LULC class. Independent variables considered unlikely to determine suitability were rejected and the regression was rerun with remaining variables. Output from the regression indicated probability (suitability) of each 250-m pixel to support a given LULC class, as

$$\theta_h = \left\{1 + \exp\left[-\propto - \sum_{k=1}^{n} \beta_k X_{hk}\right]\right\}^{-1}$$

where θ_h is the probability of that pixel being a member of class h, with a value ranging from 0 to 1, $\propto$ is the intercept, β_k is the regression coefficient for independent variable k, and X_{hk} is the value of independent variable k. Each suitability surface and the underlying statistical relationships were scrutinized by a group review involving all project personnel. Each of the >1300 suitability surfaces were reviewed on large display screens and compared to existing LULC distributions and independent variables used in the logistic regression. If issues were identified in the statistical analysis or in the resulting image's representation of suitability for a given LULC class, suitability surfaces were rejected and the logistic regressions were redone. This procedure not only improved the fidelity of each suitability surface, but also helped to calibrate individual analysts who were producing suitability surfaces. Creating individual suitability surfaces tailored to each ecoregion was time consuming, but allowed for a high quality representation of landscape pattern not only across the conterminous United States, but within each ecoregion. Given the very large number of suitability surfaces produced, it is not practical to provide comprehensive information here on the statistical characteristics of all the logistic regressions or the resultant suitability surfaces.

The placement of a LULC patch on the landscape began with the placement of a "seed" pixel on the suitability surfaces. Seed pixels marked the center of a new LULC patch. Depending upon the scenario, the LULC type being modeled, and the characteristics of the underlying suitability surface, a "clumpiness" parameter was used that determined what range of values on a suitability surface's histogram were available for the placement of a seed pixel. For example, urban land patterns are typically clumped, with new urban lands typically occurring in close proximity to existing urban lands. To ensure a clumped spatial pattern for the urban LULC class, the clumpiness parameter was used to restrict placement of new urban patches to areas where suitability values are very high (i.e., only using the top of the urban suitability surface's histogram). Conversely, where the pattern of a given LULC class was more dispersed, a more relaxed clumpiness setting allowed the placement of new LULC patches on a much wider portion of the suitability surface histogram. FORE-SCE first used the clumpiness parameter to mask unsuitable locations, and then stochastically selected a seed pixel within the remaining suitable locations. FORE-SCE then consulted the assigned patch size distribution for that ecoregion and LULC class, and stochastically selected an appropriate patch size from that distribution. The patch was then placed on the landscape, with the seed pixel at the patch's center. If the placed patch spatially fell over areas deemed to be unsuitable for that LULC class, those pixels within the patch were eliminated. The process then continued with the next patch, continuing sequentially through each modeled LULC class until demand for a given year was met. Processing then moved to the next year and the process was repeated.

In addition to modeling the thematic LULC classes in Table 1, FORE-SCE tracked and modeled forest stand age. A starting map of forest stand age for 1992 was generated with VCT data (Huang et al. 2010), and the U.S. Forest Service's forest inventory and analysis (FIA) data (*available online*).[8] VCT-identified clearcuts were used to establish starting stand age for all areas disturbed between 1984 and 1992, while an interpolated surface of FIA data points was used to fill in forest age in areas not recorded as disturbed in the VCT. FORE-SCE tracked forest stand age for each yearly model iteration and reset the stand age to zero whenever a forest was clear-cut, or when afforestation resulted in a new forest patch. The forest-age layer was also used to ensure realistic cutting cycles. For example, in ecoregions of the Pacific Northwest where commercial forestry is dominated by Douglas-fir (*Pseudotsuga menziesii*), FORE-SCE only allowed clear-cutting of evergreen forest patches for stand ages of 50 yr or higher, to mimic realistic cutting cycles in the region. Cutting cycle intervals were set independently for each forest class and for each ecoregion, based upon regional forestry characteristics.

The PAD-US data were used to control LULC change within protected areas. FORE-SCE used spatial masks constructed from appropriately attributed PAD-US polygons to restrict certain forms of land-use transitions. The PAD-US database provided four levels of management using GAP (USGS gap analysis program) status, a ranked conservation measure for each parcel in the PAD-US database. GAP status 1 indicated permanent protection, managed for most natural state, GAP status 2 indicated permanent protection, where management is allowed, GAP status 3 indicated protected, but managed for multiple uses, and GAP status 4 indicated not protected. The economically oriented A scenarios had lands with GAP status 1 and 2 protected, whereas the environmentally oriented B scenarios had GAP status 1, 2, and 3 protected. In all scenarios, areas of GAP status 1 were protected from all forms of LULC conversion other than potential natural vegetation succession. In the scenarios in which they were used, GAP status 2 and 3 lands were protected from changes to other anthropogenic land uses (e.g., forest to agriculture or forest to urban). However, as some forms of protected status 2 and status 3 lands are often used for forest harvest (e.g., national forest lands), clear-cutting was still allowed on these lands. PAD-US data were also used to partition forest land into the three ownership types of private land, national forest land, and other public land. This allowed for the independent parameterization and modeling of forest cutting based on forest ownership characteristics.

FORE-SCE model runs began in 1992, using the modified 1992 NLCD as the base LULC layer, along with the initial 1992 forest stand-age layer. Modeling results included: (1) annual LULC maps from 1992 to 2100 at a 250-m spatial resolution and with a thematic resolution corresponding to the classes in Table 1, with four scenarios from 2006 to 2100; and (2) annual, 250-m resolution images representing forest stand age for forested pixels (includes the deciduous, evergreen, and mixed forest classes, and forested wetland).

[8] http://www.fia.fs.fed.us/tools-data

Model validation and assessment

Comparison of model results with NLCD.—Assessment of LULC model performance has often relied on traditional validation techniques used for temporally static maps. Modeled results for a historical period are typically compared to historical LULC maps, and traditional assessment measures, such as kappa indices or user's and producer's accuracy, are often used (Pontius et al. 2008). For practical applications, however, a formal validation of LULC models is often difficult. We focused on the concepts of quantity disagreement and allocation disagreement, measures with considerable advantages over a measure such as kappa (Pontius and Millones 2011). Quantity disagreement between a modeled and reference map refers to map differences due to an imperfect match in overall proportions of LULC. Allocation disagreement refers to map differences due to an imperfect match in the spatial arrangement of LULC.

Challenges for this application included the choice of validation methodology, availability of suitable reference data, and the difficulty of validating data with such a broad thematic, spatial, and temporal scope. For the 2006–2100 projections, there was little value in validating quantified scenarios based on qualitative storylines (Pontius and Neeti 2010). Quantity disagreement can be assessed for the historical 1992–2005 period. However, for this application, the quantity of LULC modeled was set by the historical remote sensing data (land cover trends or NLCD). FORE-SCE is designed to precisely match prescribed levels of demand, as shown by past applications (Sohl et al. 2012*a*, *b*). Validation of quantity disagreement due to the modeling methodology is thus not discussed in this paper.

With demand parameterized individually for each ecoregion, allocation disagreement is only an issue within an ecoregion's boundaries. Allocation disagreement can be determined if reference data are available. However, data set inconsistencies between the different NLCD versions and with the USGS land-cover trends data hindered the assessment of modeling results. The USGS land-cover trends data are sample based and provide inadequate spatial coverage to assess allocation disagreement. NLCD provides wall-to-wall LULC data for 1992, 2001, and 2006, but because of changes in mapping techniques and classification systems, direct pixel-by-pixel comparison between the three NLCD dates is not possible. Our starting 1992 LULC was based on the original 1992 NLCD product (Vogelmann et al. 2001). There are no NLCD change data based on the original 1992 NLCD; USGS land-cover trends data were used to drive demand for LULC change for the 1992–2000 period. A retrofit NLCD product exists to assess change between 1992 and 2001, but the original and retrofit 1992 NLCD versions differ substantially at the pixel level (just ~78% agreement for eight aggregated LULC classes).

Not only are methodologies and classification systems different between mapping frameworks, but the largest LULC change by area, forest clearcuts, is treated differently between land-cover trends, the three NLCD versions, and FORE-SCE. All NLCD products other than the original 1992 NLCD map cover for forest use areas, with recent clearcuts represented by the stage of vegetative regrowth since cutting (often patches of "barren" or "grass/shrub"). This model application specifically models clear-cut forest patches as a distinct class. Given the inherent differences between data sets, any comparison between the model results and NLCD must be considered as more of a consistency check than a formal validation. We compared model results to the 1992–2001 NLCD retrofit data by examining quantitative differences in modeled vs. NLCD change. We also provide a county-level comparison of the two largest net LULC changes for 1992–2001, urban growth and forest clearcuts.

Qualitative and quantitative scenario comparison.—Map comparison tools can also be used to compare scenario projections, and to quantify whether differences between modeled scenarios are due to quantity disagreement (specified scenario demand) or to allocation disagreement (where FORE-SCE spatially allocates change; Pontius and Millones 2011). We compared modeled IPCC SRES scenario pairs over time, and quantified the source of differences between modeled maps. A spatial diversity image was also constructed by tallying the number of different LULC classes found at a given pixel between the four scenarios. This was used to assess spatial variability between scenarios.

Comparison to other model frameworks.—We also compared FORE-SCE scenarios with results from other modeling frameworks. Several other modeling efforts have produced LULC projections for the conterminous United States, but provided different levels of spatial and thematic detail compared to this work. The most similar modeling efforts in scope are likely those produced by Wear (2011) and Radeloff et al. (2012). Both approaches use an econometric model to produce county-level estimates of land use, but the Radeloff projections also used a land-capability class to guide sub-county placement of LULC change. Both the Wear and Radeloff projections are much coarser thematically than this work (five LULC classes for each vs. 17 for this work). The Wear projections are provided at the county level, but the Radeloff projections are pixel-based and finer in spatial resolution than this work (100 m vs. 250 m).

Other LULC projections also exist for the conterminous United States, but they are typically very different in (1) spatial scale, with either very coarse spatial resolution or nonspatial projections of land-use proportions, (2) thematic resolution, with many approaches limited to modeling one class (e.g., urban models), or (3) spatial extent, with projections covering only small regions. The IMAGE model, used as one data source in the scenario construction, has modeled the entire conterminous United States. The forest and agricultural sector optimization model (FASOM) is a partial equilibrium economic model that has widely been used to model detailed thematic changes in the agricultural and forest sectors, but the data are not spatially explicit, with projections for states or other large regions (Adams et al. 1996, U.S. EPA 2005). Bierwagen et al. (2010) produced a national set of spatially explicit scenarios of housing and impervious surface extent, but the scenarios do not model other LULC changes. Other urban area (single LULC class) projections also exist at the county level (Nowak and Walton 2005), while countless studies provide local- or regional-scale projections for portions of the United States. Other integrated modeling frameworks provide coarse-level LULC data for the globe, such as harmonized land-use data from 1500 to 2100 (Hurtt et al. 2011), but these data are thematically coarse and use LULC classes such as "primary" and "secondary" land, which makes comparison to these results impossible.

Several characteristics of the various studies complicate the direct comparison of results, including (1) definitional differences between major land-use classes, (2) different source data resulting in variable starting land-use proportions, and (3) the use of different scenarios and scenario assumptions. However, we provide a comparison of results from several different modeling frameworks, and discuss model implications.

Results

Modeling results

Projected land-use and land-cover maps.—Table 1 provides a summary of the spatially modeled LULC data for the conterminous United States, with per-class change for the historical period from 1992 to 2005, and projected change from 2005 to 2100 for each of the four scenarios. The historical period is discussed in greater detail in the model validation and assessment section. For the 2005–2100 projections, major differences between scenarios can be identified by examining trends in natural (water, barren, forest, grassland, shrubland, and wetland) vs. anthropogenic (urban, mining, and agricultural lands) LULC classes. Urban development increased in all scenarios, but with higher growth in the economically focused A scenarios. The A1B and B1 scenarios each had the same global population assumptions (population increase to 8.7 billion by 2050, declining to 7 billion by 2100; Nakicenovic et al. 2000), yet the area of new urban lands was lower in the B1 scenario due to a focus on environmentally friendly lifestyles and "smart" urban growth. The B2 scenario had the second highest population growth at a global level (steady increase to 10.4 billion by 2100), yet the projected U.S. population was the lowest of all four scenarios, due to an economic focus on regionalization and much lower in-migration to the United States. As a result of low population pressure as well as the B2 scenario's focus on environmental protection, urban growth was the smallest of all four scenarios. The A2 scenario assumed high economic growth and very high population growth globally (15 billion by 2100), and had the highest rate of urban increase.

Forest cutting rates remained roughly similar or experienced increases in the scenarios. Very high economic growth in the A1B scenario resulted in high demand for forest products and the strongest rates of forest cutting. High energy demands and high technological innovation in the A1B scenario also resulted in the assumption of high use of biofuels, including cellulosic biofuels that impacted forest harvest. Agricultural lands (cropland and hay/pasture) increased substantially in the A scenarios, with a more modest increase in the B1 scenario and a modest decline in the B2 scenario. In sum, anthropogenic landscapes experienced general increases in all scenarios, with the exception of the B2 scenario, where relatively low urban expansion was more than offset by the loss of agricultural land. Natural landscapes experienced general declines in all scenarios other than B2. Due to conversion of forested lands to urban and agricultural land uses, forest declined in all scenarios but B2. Grassland and shrubland similarly declined in all scenarios other than B2. Wetland classes declined in both the A scenarios, but a desire to maintain and restore wetlands under the environmentally friendly B scenarios resulted in modest increases in wetland extent.

Characteristics of the scenarios were apparent not only at the aggregated national scale, but in local landscape patterns. Fig. 2 depicts spatial modeling results near Columbia, South Carolina, USA showing clear differences between the four scenarios. The region experienced strong urban growth in all scenarios, but obvious differences existed between scenarios, most noticeably by 2100. The environmentally focused B1 and B2 scenarios showed much less urban growth than the economically focused A1B and A2 scenarios. As noted above, scenarios A1B and B1 each had the same population assumptions, yet the B1 scenario showed markedly less urban growth in Columbia due to the assumption that environmental concerns would drive more compact urban growth. In all scenarios, a pocket of undeveloped land existed on Fort Jackson (a military base) at the eastern edge of Columbia, with the PAD-US data used to restrict urban growth from occurring. Differences in the extent of agricultural land (cropland and hay/pasture) are also obvious in Fig. 2. The economically focused A1B and A2 scenarios showed sharp increases in agricultural land in this region, with 37% and 68% increases in agricultural land extent by 2100, respectively. The net increases in agricultural land in the A scenarios were especially notable given that much of the increase in urban lands occurred due to conversion of agricultural land to urban/developed land. The environmentally focused B1 and B2 scenarios both showed agricultural land declines, with B1 declining by 21% and B2 declining by 51%. Less obvious in Fig. 2 were the differences in forest cutting between scenarios. By 2100, the percentage of remaining forest land use classed as clear-cut was highest in the two economic scenarios, at 14% for A1B and 10% for A2, and lowest in the two environmental scenarios, at 4% for B1 and 6% for B2.

In addition to producing scenarios with different proportions of future LULC, FORE-SCE produced future landscapes with variable spatial configurations. Fig. 3 represents national-level landscape metrics over time for four major classes of vegetation, for each of the four scenarios. Mean patch size and the number of core areas (large contiguous blocks with an edge depth at least 2 km from another LULC class) reflected landscape patterns resulting from changes in overall LULC proportions (Table 1) and fragmentation of natural landscapes. Forested lands (forest use, including both forest cover and clearcuts) experienced sharp declines in mean patch size and the number of remaining core areas in the A scenarios, while remaining relatively stable in B1 and increasing modestly in the B2 scenario. Grasslands experienced sharp declines in both measures for all scenarios other than B2, where mean patch size and the number of core areas stayed relatively stable over time. Shrublands experienced much less change than the other major LULC classes, in all scenarios. The arid shrublands of the western United States are commonly not suitable for other land uses, and thus remained relatively unchanged compared to other natural LULC classes. Wetland areas experienced modest declines in mean patch size and number of core areas for both of the A scenarios, while slight increases in wetland area in the B scenarios drove slight increases in both measures.

Projected forest stand age.—Fig. 4A provides mean stand age of all forest pixels at a national level. FORE-SCE does not currently model natural mortality or the effects of other forms of disturbance, so a forest pixel will age continuously until it is disturbed (see *Data availability and applications* section about use of the stand-age data). National trends in mean stand age generally rose steadily over time, with two modeled LULC changes that could lower the increases in mean stand age: (1) clear-cutting a forest, and (2) afforestation, with both LULC changes resetting stand age to 0 yr. At the aggregate national scale, the four scenarios showed diverging patterns of mean forest stand age. The A1B scenario was characterized by a very sharp rise in forest cutting rates (Table 1), a primary reason the scenario had the lowest mean forest stand age by 2100. The B2 scenario surprisingly had the second-lowest mean stand age by 2100, due to two primary factors; (1) as a regional scenario with a focus on self-reliance and

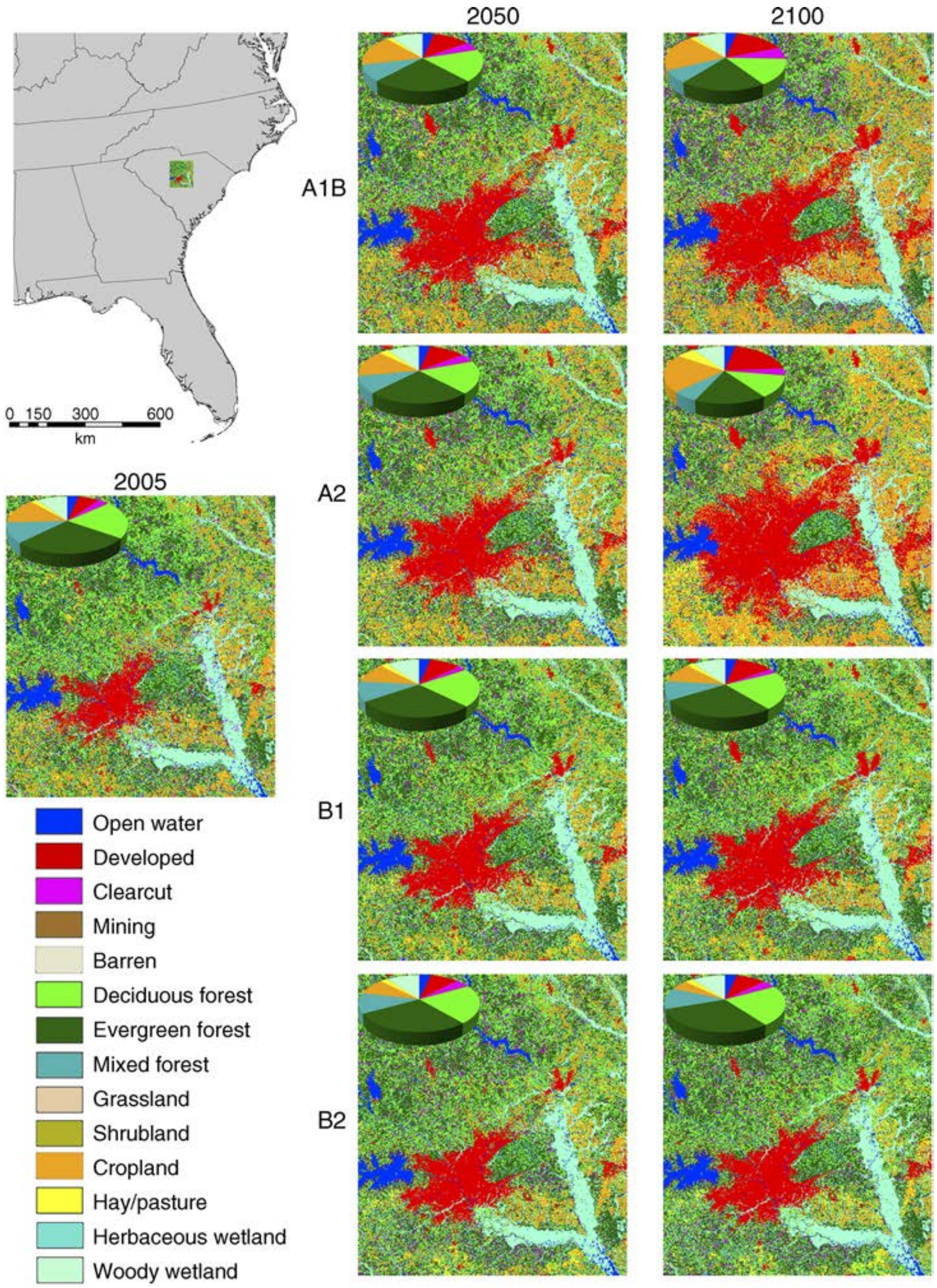

FIG. 2. LULC projections near Columbia, South Carolina, USA. Projected urban growth from 2005 to 2050 and 2100 varied between IPCC scenarios, with the economically oriented A scenarios showing much higher rates of growth than the environmentally oriented B scenarios. Differences also exist between scenarios for changes in agricultural land cover and area of forest clearcuts.

local use of resources, cutting rates were increased over historical rates, and 2) as an environmental scenario, substantial afforestation resulted in the widespread establishment of new, younger forests. Fig. 4B shows trends in overall forest area over time for the four scenarios. By multiplying mean forest age by forest area, an age-years measure can be constructed that displays an aggregate of stand ages and serves as a rough proxy for overall standing forest biomass in a scenario (Fig. 4C). In this measure, both of the environmental B scenarios had the highest accumulated age-years, with the strong growth in forest area outweighing the lower mean stand age for the B2 scenario. Conversely, both economic A scenarios had much lower accumulated age-years, with the large loss of forest land outweighing any relative ranking of mean stand age.

Table 2 provides stand-age changes between 1992 and 2100 by forest class and protection status. For all

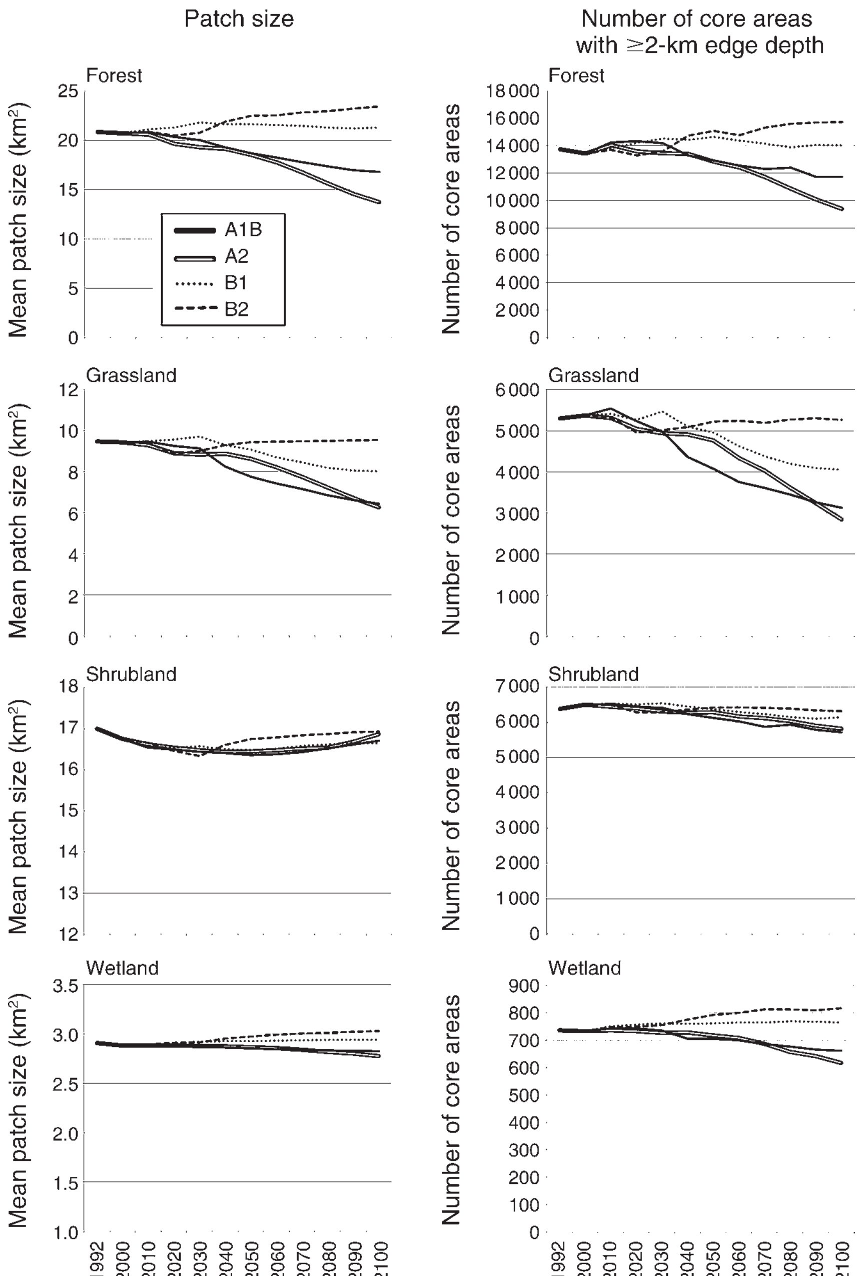

FIG. 3. Mean patch size and the number of core areas for four major LULC classes. Mean patch size represents the mean size for each LULC class for the conterminous United States. The number of core areas represents patches of contiguous pixels of a LULC type at least 2 km from any other LULC type (e.g., a 2-km edge depth). Note that the forest area represents overall forest land use, including the aggregated deciduous, evergreen, and mixed forest classes, as well as the three clearcut classes. Wetland represents the aggregated woody and herbaceous wetland classes.

scenarios and forest classes, forest lands with a protected status showed a much higher initial stand age than unprotected forest lands, evidence of the legacy of historical protected status on current stand ages. Initial 1992 stand-age differences between protected and unprotected lands were highest for evergreen forest, with protected lands showing a mean stand age over 40 years higher than unprotected lands. Evergreen forest had more land in protected status than the other three forested classes combined, for both A scenarios (GAP status lands 1 and 2 protected) and B scenarios (GAP status lands 1, 2, and 3 protected). Initial stand-age differences between protected and unprotected lands were much lower for other forest classes.

Forest in both protected and unprotected status showed gains in stand age, but the magnitude of changes

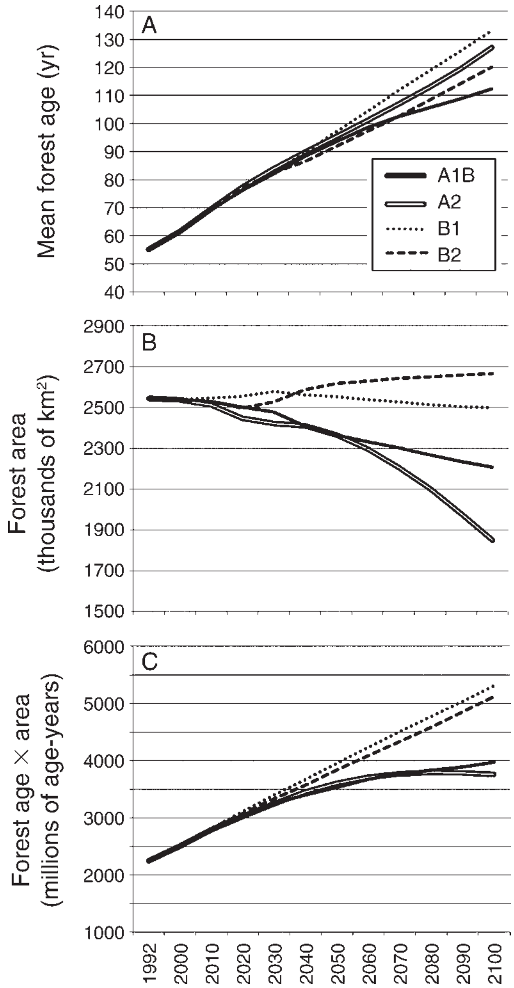

FIG. 4. Forest stand-age characteristics for the conterminous United States for each of the four scenarios, representing (A) mean stand age for the three forested classes from Table 1 (deciduous, evergreen, and mixed forest), (B) overall forest area for the three forest classes, and (C) an aggregated age-years measure (presented in yr) that multiplies forest age (yr) by forest area (km^2).

differed substantially between classes (Table 2). The largest increases in stand age occurred with woody wetland classes (both protected and unprotected). Although woody wetland extent declined substantially in the A1B and A2 scenarios due to land-use conversion (Table 1), the remaining woody wetlands in 2100 had relatively little disturbance through clear-cutting, and little new woody wetland was established. As a result, stand-age increases for woody wetland were near the 108-yr maximum stand-age increase for the 1992–2100 period. Across all four scenarios, evergreen forest generally had the smallest net increases in stand age. The amount of clear-cutting varied by scenario, but heavy clear-cutting occurred in all scenarios in the southeastern United States, where plantations of evergreen species are managed as a crop, with short rotation cycles. Commercial forestry also results in substantial clear-cutting of evergreen species in the Pacific Northwest. Protected evergreen forest lands included national forest lands, where clear-cutting is a common forestry practice; therefore, despite 40% and 51% of evergreen forest land in protected status in the A and B scenarios, respectively, evergreen stand-age increases were relatively low in both protected and unprotected status lands. While clear-cutting accounted for much of the lower stand-age increases for evergreen forests, afforestation (creation of new, young forests) also lowered stand-age increases for evergreen forest in the B scenarios, especially with the extensive conversion of agricultural land to evergreen forest in the B2 scenario.

In examining stand-age distributions for aggregate forest area over time (Fig. 5), the shift in magnitude for the modal peak for a given scenario and protected status demonstrates the effects of clear-cutting as well as deforestation. For the A2 scenario, for example, the area covered by the modal stand age for unprotected forest in 1992 was ~42 500 km^2, but only about ~14 000 km^2 remained in 2100, indicating that >28 000 km^2 of the 1992 forest pixels were disturbed (clear-cut) or were converted to another LULC class by 2100. The modal peak values for unprotected forest also declined for the

TABLE 2. Area, starting stand age, and 1992–2100 stand-age change by forest type and protected land status.

Forest type and protected status	1992 A scenarios: Area (1000 km^2)	1992 A scenarios: Stand age (yr)	1992 B scenarios: Area (1000 km^2)	1992 B scenarios: Stand age (yr)	2100 stand age (yr): A1B	A2	B1	B2	1992–2100 net change in stand age (yr): A1B	A2	B1	B2
Deciduous												
Protected	96	59	149	56	149	154	151	147	+91	+95	+95	+91
Unprotected	821	44	768	43	98	106	124	112	+57	+63	+81	+69
Evergreen												
Protected	412	98	518	95	162	173	177	167	+63	+75	+82	+72
Unprotected	599	58	493	52	109	123	115	100	+51	+65	+63	+48
Mixed												
Protected	38	62	58	58	149	154	150	144	+88	+92	+92	+86
Unprotected	297	42	277	41	80	89	107	94	+39	+48	+67	+53
Woody wetland												
Protected	33	47	61	48	153	153	153	152	+107	+107	+105	+104
Unprotected	181	42	153	40	144	144	140	134	+102	+102	+99	+94

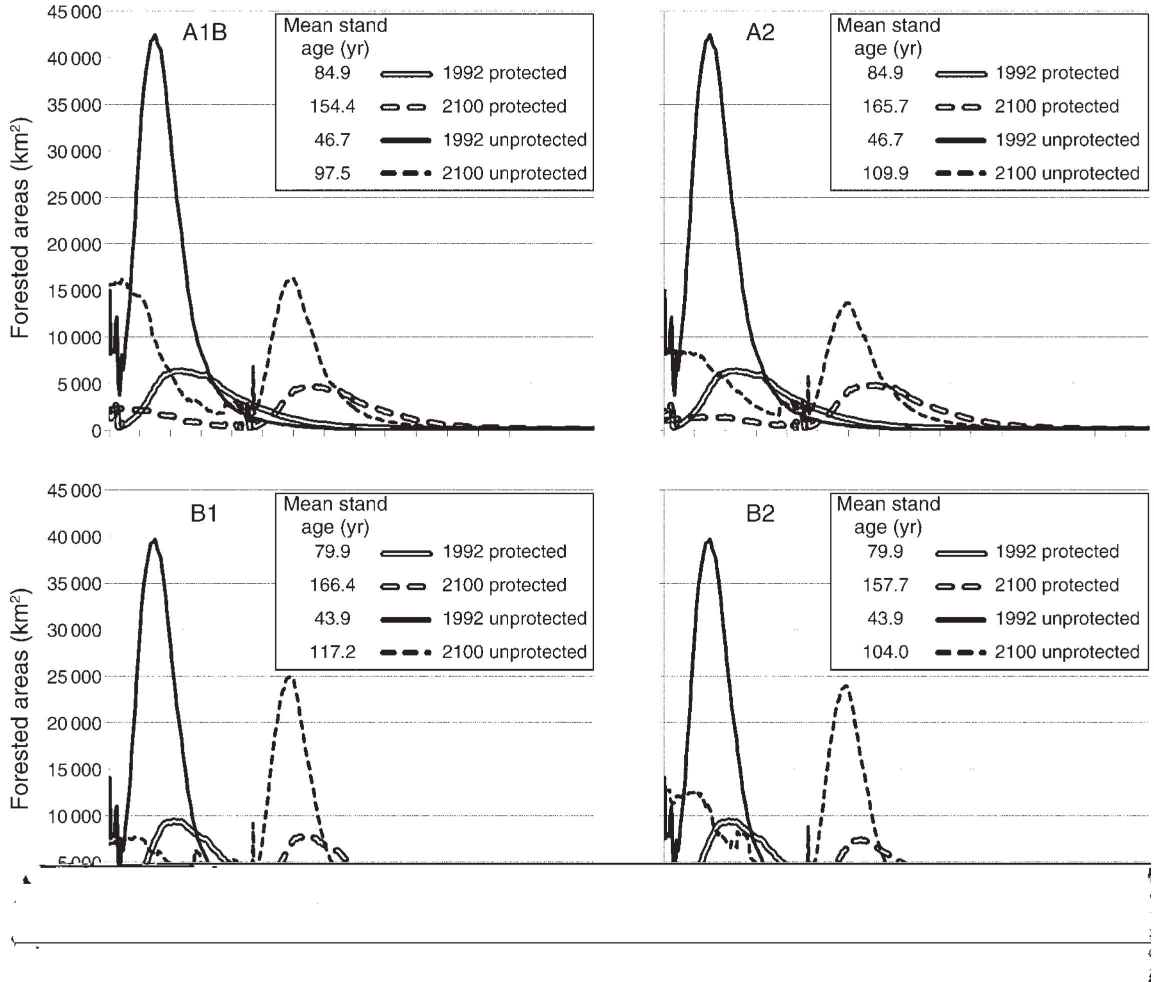

FIG. 5. Stand-age distribution changes from 1992 to 2100 for protected and unprotected forest lands in aggregate, for each of the four IPCC SRES scenarios. Protected lands include PAD-US gap analysis program (GAP) status lands 1 and 2 for the A1B and A2 scenarios, and GAP status lands 1, 2, and 3 for the B1 and B2 scenarios.

B scenarios, but not nearly as sharply, indicating fewer disturbances. Protected forest lands showed a much more uniform shift to older stand ages, with fewer disturbances and less of a decline in the modal peak value. The amount of young forest land in 2100 was due to either clear-cutting that reset stand age, or to afforestation. In the A1B scenario, a strong new peak of young forest ages appeared for unprotected lands in 2100, with most of these young forests representing clearcuts on private lands (particularly in the southeastern United States). In the B2 scenario, a similar strong peak of young forest ages appeared in 2100, but both clear-cutting and substantial afforestation in the B2 scenario influenced the magnitude of that peak. Note that GAP status 1 lands, protected from anthropogenic LULC change including clear-cutting, behaved as expected, with mean forest age increasing exactly one year for every simulated model year (not shown in Fig. 5).

Spatial patterns of changes in stand age are shown in Fig. 6, which depicts mean stand-age changes for each of the 84 Level III ecoregions. Agricultural regions where forest is a minor component of the landscape generally showed strong increases in mean forest stand age, primarily because little forestry activity occurred in these regions, and any forest disturbance that did occur was primarily conversion of forest land to urbanized land or to agriculture. Stand-age increases were also strongest in forested areas where forestry was not a major economic activity, such as in the southern Rockies or in ecoregions with a large area of protected lands. Ecoregions with the lowest increases, or even net decreases in mean stand age, were those where forest cutting rates were very high, particularly in the southeastern and northwestern United States. Forest cutting rates had a strong effect on patterns of forest stand age, and forest cutting tended to occur in the same regions regardless of scenario, so overall spatial patterns

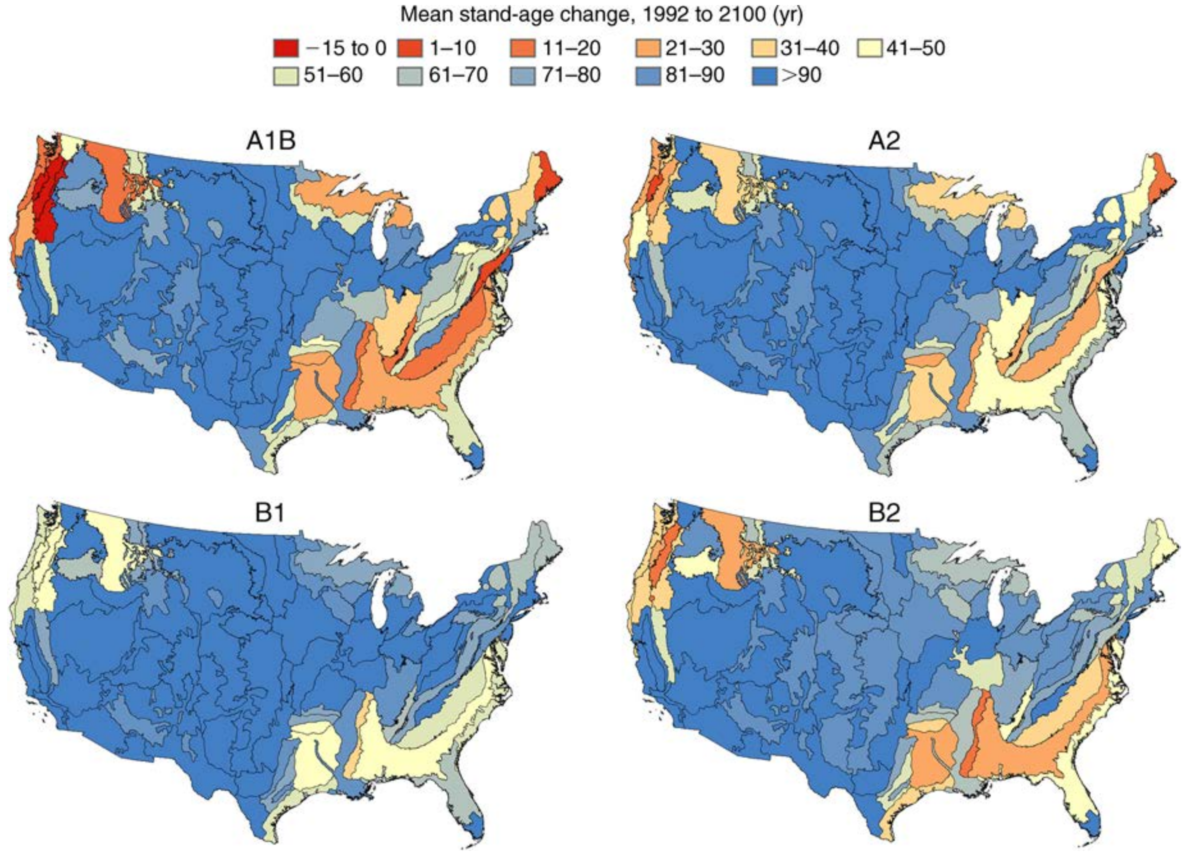

FIG. 6. Changes in mean forest stand age by Level III ecoregion (indicated by black outlines; U.S. EPA 1999). Values for each ecoregion represent the difference in mean stand age between 1992 and 2100, across the three major forest types presented in Table 1 (deciduous, mixed, and evergreen).

were relatively similar between scenarios, although the magnitude of stand-age changes differed. Despite FORE-SCE continuously aging all non-disturbed forest pixels, in the A1B scenario, heavy cutting rates resulted in some ecoregions experiencing negligible increases to even negative changes in mean forest stand age by 2100. Both A scenarios had very high demand for both agricultural and forest products, with agricultural expansion pushing forestry activity to more marginal areas for silviculture, such as the Northeast or upper Midwest. As a result, mean forest stand-age increases were much lower in those regions in the A scenarios than in the B scenarios, even with the strong forest cutting demand in the B2 scenario.

Assessment of modeling results

NLCD comparison.—The 1992–2001 period was used to compare modeled LULC vs. the 1992–2001 retrofit NLCD data. Given differences in starting LULC proportions (e.g., as noted above, the two data sets only agree at ~78% at the pixel level, and the original 1992 NLCD had less than half the mapped urban land as the retrofit 1992 NLCD), the focus for comparison was on the distribution of LULC change. Tables 3 and 4 provide a quantitative comparison of modeled and NLCD change for 1992–2001, with modeled LULC aggregated to the eight classes represented in the NLCD data. While the overall amount of LULC change is similar in Table 3 (3.17% modeled vs. 3.06% mapped by NLCD), quantitative differences existed for both net changes in LULC classes (Table 3) as well as individual LULC transitions (Table 4). Some differences are due to the respective paradigms for modeling forest clear-cutting, with the very high changes in forest and grass/shrub in NLCD (Tables 3 and 4) strongly affected by the cover-based mapping of clear-cutting (e.g., clearcuts represented as forest transitioning to grass/shrub). However, differences in other classes cannot be explained by the respective mapping paradigms, as transitions between water, forest, agriculture, and wetland are quite different between the two data sets (Table 4). These differences directly reflect measurement differences between the USGS land-cover trends data (data used to define demand for the modeling) and the NLCD retrofit data. Given the desire to assess modeling results and not differences among other data sets, the assessment thus focused on classes and transitions with similar quantitative characteristics between the modeled

TABLE 3. Overall net change (in 1000 km^2) from 1992 to 2001 in land-use and land-cover (LULC) classes, using modeled LULC vs. NLCD data.

Source	Water	Urban	Barren	Forest	Grass/Shrub	Ag	Wetland	Ice/Snow	Clearcut	Change (%)
Model	1.7	23.7	2.1	−8.2	3.5	−24.2	−1.6	0.0	3.0	3.17%
NLCD	6.7	18.1	3.9	−61.9	30.4	−7.4	10.1	0.2	N/A	3.06%

and NLCD retrofit data. A closer look at the data tables shows some forms of LULC conversion were roughly similar between data sets. Urban land increased 18 062 km^2 in the NLCD and 23 736 km^2 in the modeled data. Clearcut quantities were also comparable. In the cover-based mapping of NLCD, the "forest to barren" and "forest to grass/shrub" transitions mostly represented the change in existing cover when a clearcut occurred, with a total amount of 58 175 km^2 from 1992 to 2001. The modeled data showed a similar amount of 60 405 km^2 of forest transitioning to clearcuts. Other major LULC transitions were not nearly as consistent between data sets. For this study, an examination of the spatial differences between the modeled data and NLCD thus focused on new urban lands and forest clearcuts.

Fig. 7 provides a spatial representation of differences in FORE-SCE vs. NLCD LULC at the county level for new urban land and forest clearcuts. With demand for modeled LULC change parameterized individually for each ecoregion, quantity disagreement between the modeled data and the NLCD would be reflected by an overall positive or negative bias for counties within an ecoregion. Allocation disagreement would be reflected in a heterogeneous pattern within a given ecoregion.

Both quantity and allocation disagreement are suggested in Fig. 7 for 1992–2001 urban change. Modest quantity disagreement is suggested for new urban lands

TABLE 4. Quantitative differences between modeled LULC changes from 1992 to 2001 vs. the 1992 to 2001 NLCD change data.

	Change from 1992 to 2001 (1000s of km^2)									
Source	Water	Urban	Barren	Forest	Grass/Shrub	Ag	Wetland	Ice/Snow	Clearcut	Total
A) Model (FORE-SCE)										
Water	(225.8)	0.0	0.2	0.0	0.4	0.1	1.3	0.0	0.0	227.8
Urban	0.0	(171.8)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	171.8
Barren	0.2	0.1	(115.9)	0.2	0.4	0.1	0.1	0.0	0.0	117.0
Forest	0.3	7.1	1.2	(2184.8)	1.1	5.2	0.3	0	62.9	2263.0
Grass/Shrub	0.5	3.2	1.2	0.6	(2623.3)	25.8	0.7	0	0.1	2655.4
Ag	0.9	12.6	0.5	8.6	32.6	(2005.7)	1,2	0.0	0.1	2062.2
Wetland	1.6	0.6	1.2	1.5	0.7	0.9	(300.7)	0.0	7.8	312.6
Ice/Snow	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(1.5)	0.0	1.5
Clearcut	0.0	0.2	0.0	60.4	0.4	0.2	6.6	0.0	(2.1)	69.9
Total	229.4	195.6	119.1	2254.7	2658.9	2038.0	310.9	1.5	72.9	(7881.1)
B) NLCD retrofit data										
Water	(207.9)	0.1	1.2	0.4	1.4	1.1	2.1	0.0	N/A	214.2
Urban	0.3	(393.0)	0.0	0.4	0.3	1.2	0.3	0.0	N/A	395.6
Barren	0.6	0.1	(91.4)	0.1	0.8	0.2	0.1	0.0	N/A	93.4
Forest	1.0	8.5	2.4	(2037.8)	55.8	24.9	5.9	0.0	N/A	2136.4
Grass/Shrub	3.1	3.7	1.5	16.1	(2785.7)	27.5	4.4	0.3	N/A	2842.3
Ag	6.3	7.2	0.6	17.3	26.2	(1760.5)	7.3	0.0	N/A	1825.5
Wetland	1.7	0.9	0.2	2.4	2.3	2.7	(362.1)	0.0	N/A	372.4
Ice/Snow	0.0	0.0	0.0	0.0	0.1	0.0	0.0	(1.2)	N/A	1.4
Clearcut	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	(N/A)	0
Total	221.0	413.6	97.3	2074.5	2872.7	1818.1	382.4	1.6	0	(7881.2)
C) Difference, model − NLCD										
Water	(17.8)	−0.1	−1.0	−0.3	−1.1	−1.0	−0.8	−0.0	0.0	13.5
Urban	−0.3	(−221.2)	−0.0	−0.4	−0.3	−1.2	−0.3	0.0	0.0	−223.8
Barren	−0.4	0.0	(24.5)	0.1	−0.4	−0.1	−0.1	−0.0	0.0	23.6
Forest	−0.7	−1.4	−1.2	(146.9)	−54.7	−19.7	−5.6	−0.0	62.9	126.5
Grass/Shrub	−2.6	−0.5	−0.3	−15.5	(−162.5)	−1.7	−3.7	−0.3	0.0	−186.9
Ag	−5.3	5.3	−0.1	−8.7	6.4	(245.2)	−6.1	0.0	0.1	236.7
Wetland	−0.1	−0.3	−0.1	−2.2	−1.6	−1.9	(−61.4)	0.0	7.8	−59.8
Ice/Snow	−0.0	0.0	−0.0	−0.0	−0.1	−0.0	−0.0	(0.3)	0.0	0.1
Clearcut	0.0	0.2	0.0	60.4	0.4	0.2	6.8	0.0	(2.1)	69.9
Total	8.5	−218.1	21.8	180.2	−213.8	219.9	−71.5	−0.0	72.9	

Notes: Column headings refer to 2001 values, row headings refer to 1992 values. Modeled change (A) shows a change matrix for the FORE-SCE modeled LULC. NLCD change (B) shows a change matrix for the 1992–2001 NLCD retrofit data. Modeled − NLCD (C) difference shows transition-by-transition differences between FORE-SCE and NLCD. Note that all classes besides clearcut are the mapped NLCD classes, with modeled data aggregated to match. The clearcut class appears only in the modeled data (elsewhere N/A, not available). Values in parentheses represent areas that have not changed LULC class between 1992 and 2001.

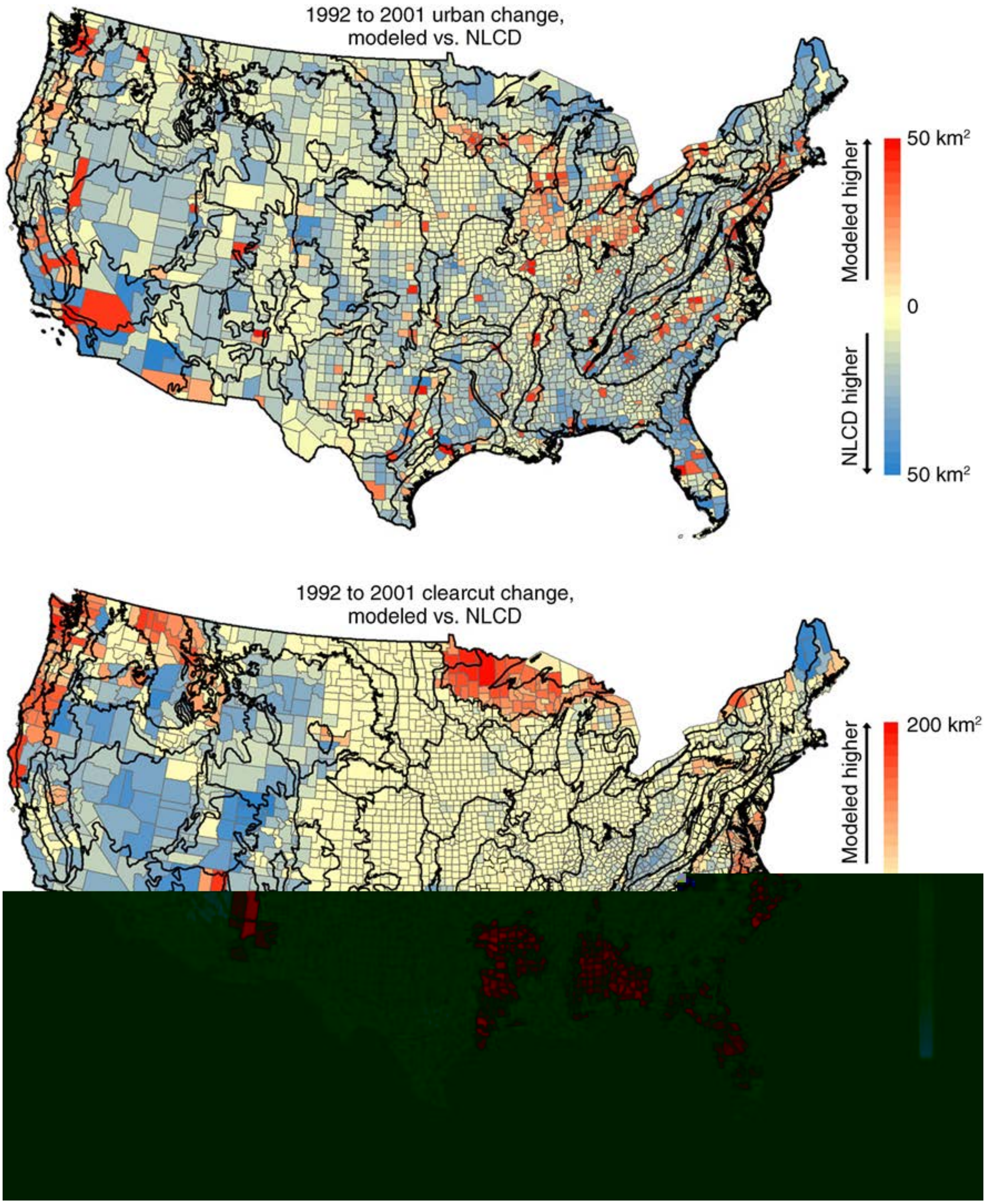

FIG. 7. Quantitative differences in the amount (km^2) of modeled LULC change for 1992 to 2001 versus that mapped by the 1992–2001 NLCD retrofit change data. The top map depicts differences in urban/developed lands, while the bottom map depicts differences in forest clearcuts.

in ecoregions of the upper Midwest and in the small ecoregions of the upper- to mid-Atlantic, where a generally consistent red pattern indicates higher overall demand for new urban lands in the model vs. NLCD. However, spatial heterogeneity within several ecoregions suggests allocation disagreement in many locations. In general, counties centered on large metropolitan areas showed higher modeled urban increases, while the NLCD showed modestly higher urban increases in most rural areas. Differences in the spatial allocation of new urban lands can be attributed to both model performance, and to differences between the original and

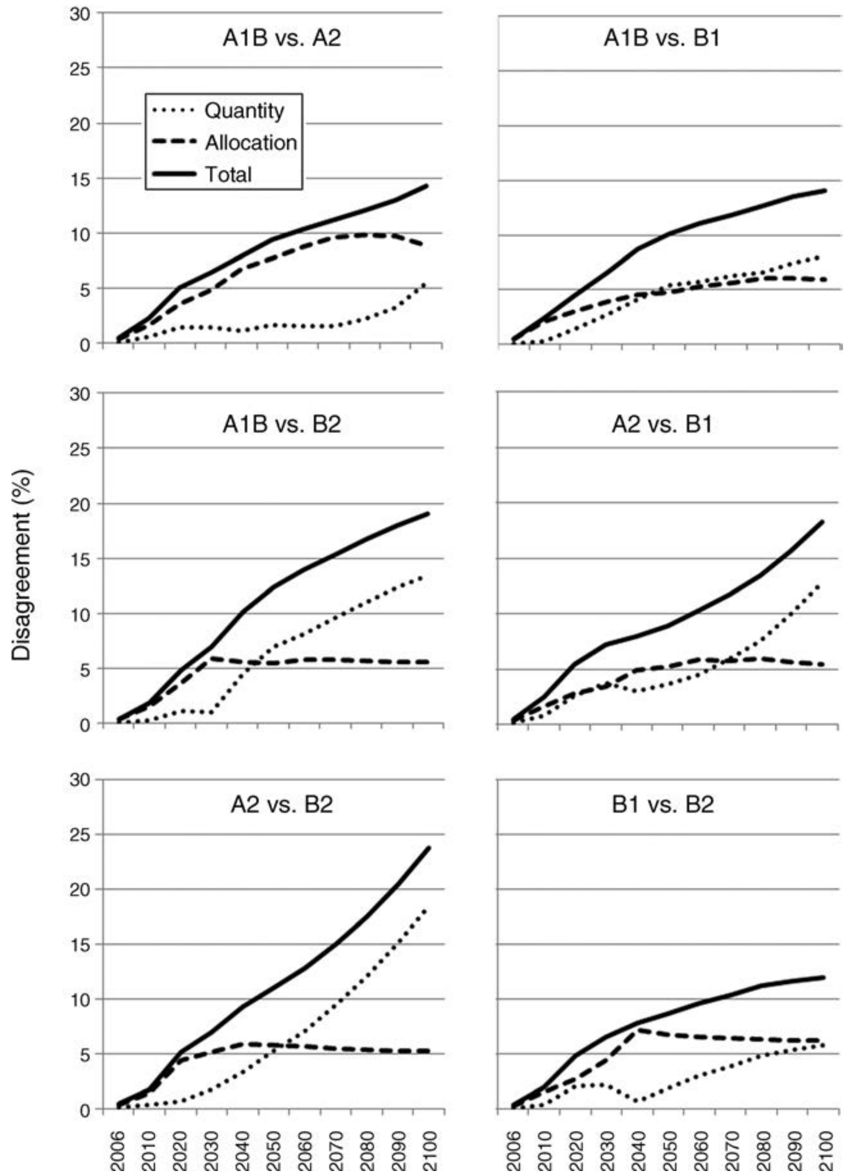

FIG. 8. Quantity and allocation disagreement over time between scenario pairs for the conterminous United States. Quantity disagreement refers to differences between a modeled and reference map due to an imperfect match in overall proportions of LULC. Allocation disagreement refers to map differences due to an imperfect match in the spatial arrangement of LULC. Allocation disagreement is generally higher than quantity disagreement during the early part of the projections. Quantity disagreement grows in importance as the simulations progress.

retrofit NLCD versions. With over twice as much urban land in the retrofit 1992 NLCD vs. the original NLCD used for this assessment, many new modeled urban patches were filling in highly suitable areas that were already classed as urban in the retrofit NLCD. Counties in and around major urban centers thus had more new urban land appearing in the modeled data vs. the retrofit NLCD. Overall, the retrofit NLCD also had a much more dispersed pattern for new urban pixels, resulting in more new urban pixels away from urban centers than in the modeled data.

Quantity disagreement with the NLCD was most evident in the map of clearcuts (Fig. 7), with more subtle allocation disagreement apparent. Several ecoregions in the Pacific Northwest, the Southeast, and near Lake Superior showed consistently higher amounts of forest clearcuts in the FORE-SCE data vs. NLCD. Many ecoregions in the interior West showed consistently lower levels in the modeled data. More modest differences are apparent in the spatial allocation of clear-cutting within an ecoregion, such as in multiple

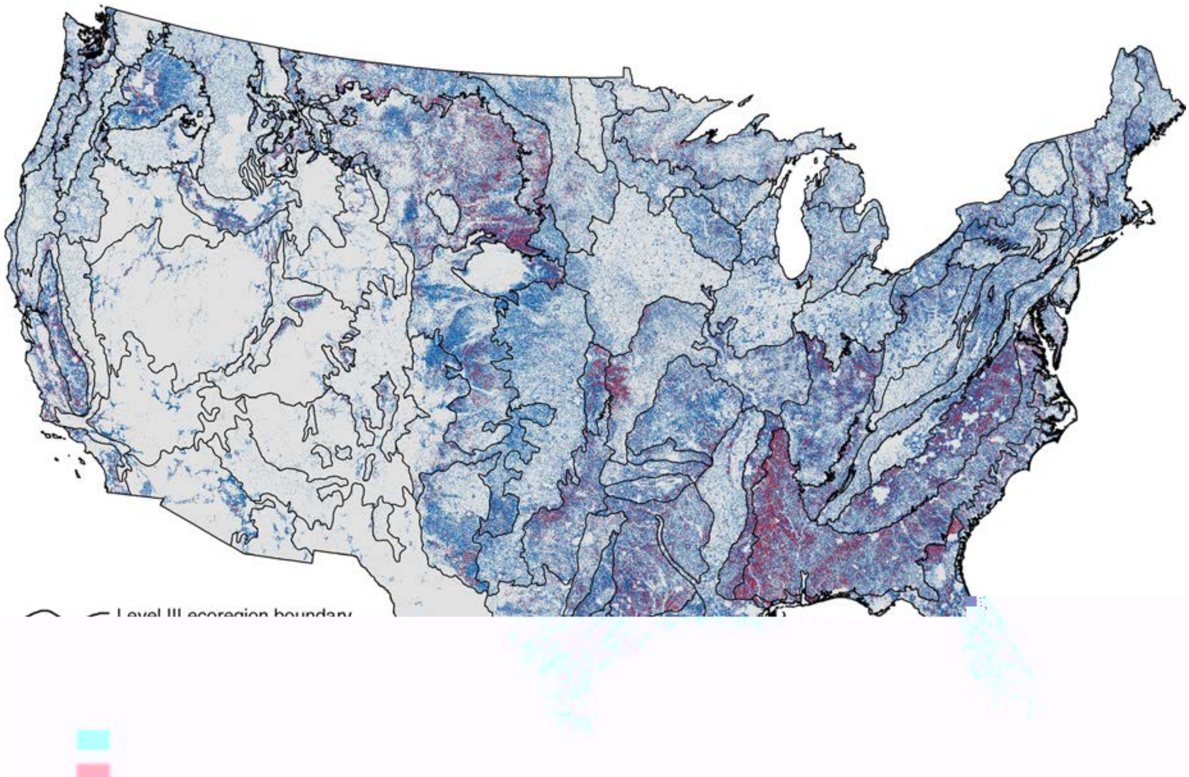

Fig. 9. Spatial diversity between scenarios for the conterminous United States for the year 2100. Differences between scenarios are low in high-value agricultural land and in arid areas of the western United States. Hotspots of diversity between scenarios are found in areas of marginal agricultural land, and in areas suitable for both agricultural and forest land uses. See U.S. EPA (1999) for description of the overlain ecoregion framework.

ecoregions in the southeastern U.S. where subregions are biased toward FORE-SCE or NLCD data.

Qualitative and quantitative scenario comparison.— Fig. 8 depicts quantity and allocation disagreement measures between each modeled scenario pair. Characteristics differ between scenario pairs, but in general, allocation disagreement is larger early in the simulation period, while differences in the scenarios themselves increasingly dominate as scenarios progress forward in time. Note that allocation disagreement is at the pixel level and does not account for "near-miss" differences in spatial allocation, where overall spatial patterns are generally similar but exact pixel placement differs slightly between model runs. In general, however, results suggest that scenario-based variability in our framework increases with simulation length, while in the shorter term, the semi-stochastic nature of the placement of LULC change patches within FORE-SCE results in allocation disagreement playing a more important role in projection differences.

A spatial diversity image is a tool that can be used to qualitatively assess spatial differences between scenarios. Fig. 9 depicts a spatial diversity image for the conterminous United States, showing pixels that had the same LULC between all four scenarios in the year 2100, or were different between two or more scenarios. We cannot specify for a given pixel whether a difference between scenarios is due to the scenario assumptions (quantity disagreement), or where FORE-SCE placed LULC change (allocation disagreement). However, areas with the same LULC regardless of scenario are assumed to be less sensitive to scenario or modeling assumptions, while areas that differ between scenarios are more sensitive. Areas where scenario or modeling assumptions had little impact on modeling results included the highest-value agricultural lands, such as the upper Midwest, portions of the Great Plains, and the Mississippi alluvial plain. These areas are currently dominated by high-productivity agricultural land, and little change between major LULC classes is likely in the future. The arid lands of the western United States were also similar in all future scenarios, as the variety of potential land uses in these areas is low. Areas with considerable differences between future scenarios were dominated by lands that are suitable for multiple land uses. Much of the southeastern United States was historically used for both agriculture and for forestry, and major differences in these land uses between scenarios resulted in a high spatial diversity in the region. Variability between scenarios was also high in

TABLE 5. Comparison of 2010–2050 FORE-SCE projections to other modeling frameworks.

Class and model framework	Area (1000s of km^2) 2010	Area (1000s of km^2) 2050	Increase	Class and model framework	Area (1000s of km^2) 2010	Area (1000s of km^2) 2050	Increase
Urban				Forest			
Wear A1B	363	579	59.4%	Wear A1B	1561	1467	−6.1%
Wear A2	357	542	51.7%	Wear A2	1565	1487	−5.0%
Wear B2	377	507	34.6%	Wear B2	1556	1501	−3.5%
Radeloff baseline	476	740	55.5%	Radeloff baseline	2099	2215	5.5%
Radeloff no farm subsidies	476	738	55.2%	Radeloff no farm subsidies	2099	2214	5.5%
Radeloff afforestation	474	730	54.0%	Radeloff afforestation	2150	2470	14.9%
Radeloff high urban rent	482	770	59.8%	Radeloff high urban rent	2094	2190	4.6%
ICLUS A1B	134	194	45.4%	IMAGE A1B	3054	2488	−18.5%
ICLUS A2	133	193	44.6%	IMAGE A2	2935	2503	−14.7%
ICLUS B1	130	174	34.3%	IMAGE B1	3042	3269	7.5%
ICLUS B2	131	182	38.7%	IMAGE B2	3017	3225	6.9%
FASOM baseline	81	356	340.0%	FASOM baseline	1368	1234	−9.8%
FORE-SCE A1B	224	360	61.1%	FORE-SCE A1B	2249	2061	−8.3%
FORE-SCE A2	219	330	50.5%	FORE-SCE A2	2235	2068	−7.5%
FORE-SCE B1	217	297	37.0%	FORE-SCE B1	2268	2270	0.1%
FORE-SCE B2	216	266	22.9%	FORE-SCE B2	2251	2304	2.4%
Cropland				Pasture/Range			
Wear A1B	1473	1403	−4.8%	Wear A1B	2079	2028	−2.4%
Wear A2	1475	1417	−3.9%	Wear A2	2081	2032	−2.3%
Wear B2	1468	1427	−2.8%	Wear B2	2078	2044	−1.7%
Radeloff baseline	1210	1053	−13.0%	Radeloff baseline	3307	3097	−6.4%
Radeloff no farm subsidies	1210	1053	−13.0%	Radeloff no farm subsidies	3308	3099	−6.3%
Radeloff afforestation	1174	870	−25.9%	Radeloff afforestation	3292	3020	−8.3%
Radeloff high urban rent	1206	1028	−14.7%	Radeloff high urban rent	3310	3112	−6.0%
IMAGE A1B	3544	4328	22.1%	IMAGE A1B	1935	1640	−15.2%
IMAGE A2	3808	4305	13.1%	IMAGE A2	2163	1769	−18.2%
IMAGE B1	3571	3495	−2.1%	IMAGE B1	2031	1497	−26.3%
IMAGE B2	3647	3234	−11.3%	IMAGE B2	2082	1332	−36.0%
FASOM baseline	1356	991	−26.9%	FASOM baseline	1538	1817	18.2%
FORE-SCE A1B	1305	1498	14.7%	FORE-SCE A1B	1954	1864	−4.6%
FORE-SCE A2	1341	1445	7.8%	FORE-SCE A2	1947	1909	−1.9%
FORE-SCE B1	1298	1298	0.0%	FORE-SCE B1	1950	1877	−3.8%
FORE-SCE B2	1322	1203	−9.0%	FORE-SCE B2	1949	1901	−2.5%

Notes: Given that other frameworks often provide results in graphical form or do not explicitly provide projections for 2010 or 2050, exact values given for non-FORE-SCE projections may be estimated from published graphs, or interpolated to the 2010 or 2050 date. As such, the data are for general comparison purposes only. ICLUS only provides urban projections, while IMAGE provides no urban projections; thus ICLUS values are shown in the urban column, while IMAGE values are absent. Projection sources below for non-FORE-SCE frameworks are Wear 2011, Radeloff et al. 2012, Bierwagen et al. 2010 (ICLUS), Strengers et al. 2004 (IMAGE), U.S. EPA 2005 (FASOM).

marginal agricultural lands (e.g., the more arid portions of the Great Plains) where agricultural land use is scenario-dependent.

Comparison with other United States LULC projections.—Table 5 provides a summary of 2010–2050 LULC projections for the FORE-SCE model results, and for several other modeling frameworks. Some general observations can be drawn from comparing overall results of the different modeling frameworks.

First, the broad, coarser scale IMAGE and FASOM models generally project higher rates of change than the econometric models or the FORE-SCE-based projections. Second, for a given modeling framework, IMAGE and FORE-SCE provide the greatest variability between scenarios, with strong shifts in both direction and magnitude of change for a given LULC class. The two econometric models (Wear and Radeloff et al.) provide the same general trajectory between their own scenarios, for all four major LULC classes, with only the magnitude of the gain or decline differing between scenarios. Third, given the variability in approaches, assumptions, and starting data, nearly all projections are remarkably similar in terms of percentage increase in urban lands. Other than the outlier of the FASOM projection (~340%), all projections are within a range of 22.9% and 61.1%, the range of values between the FORE-SCE B2 and A1B projections, respectively. Finally, cropland is the LULC class with the greatest variability between modeling frameworks. The Wear projections consistently show modest declines in cropland, while the Radeloff et al. and FASOM projections have much higher rates of declines for all scenarios. The IMAGE and FORE-SCE projections show increases in cropland for the A scenarios and flat to declining cropland for the B scenarios.

Given variable scenario assumptions, project goals, and modeling approaches, direct comparison between modeling frameworks cannot validate the performance of any one framework. Scenario-based frameworks are designed to capture the variability in potential future

PLATE 1. The Grasshopper Sparrow (*Ammodramus savannarum*) has declined considerably over the last several decades, with habitat loss a primary cause. The land-cover projections described here offer the opportunity to assess potential future impacts of land-cover change on species habitat, as well impacts on other ecological processes such as hydrology, regional weather and climate variability, and greenhouse gas fluxes. Understanding potential future impacts of land-cover change on ecological processes offers land managers and decision-makers the opportunity to potentially mitigate the negative consequences of land-cover change. Photo credit: T. L. Sohl.

landscape conditions. Variability between the four IPCC SRES scenarios mapped by FORE-SCE is comparable to overall variability between the different modeling frameworks summarized in Table 5.

Discussion

The strength of top-down, economics-based models lies in the quantification and description of forces that drive overall demand for land use (Heistermann et al. 2006). A scenario-construction process was used here that incorporated input from an integrated modeling framework to provide top-down proportions of LULC change, with overall socioeconomic assumptions from the IPCC SRES scenarios driving the major differences between scenarios. The strength of spatial allocation models is their ability to determine the suitability of the land to support a given LULC type, based on biophysical parameters (Moreira et al. 2009). The spatial allocation component of FORE-SCE determined land suitability for each LULC type, and produced realistic spatial patterns of LULC change based on historical landscape characteristics. In conjunction, the split demand and spatial allocation structure allowed for the inclusion of both top-down and bottom-up driving forces of LULC change. The projections are spatially explicit and thematically more detailed than most comparable regional- or national-scale LULC projections, resulting in an improved ability to inform ecological applications. Annual LULC maps were produced from 1992 to 2100, including the modeling of realistic proportions of underlying gross change. When compared to LULC frameworks that only provide LULC maps at two temporal endpoints or other frameworks that only model net change between major LULC classes, we are better able to inform applications where a complete accounting of all LULC change is important, such as the examination of LULC effects on carbon and GHG fluxes. Unlike other spatially explicit modeling projections for the United States, FORE-SCE tracks and models forest stand age, which is invaluable for not only improving our own model performance by allowing us to better replicate realistic forest harvest cycles, but also for informing ecological applications that require information on forest structure. The general framework used to produce these projections is flexible and transportable, and could be used to produce LULC projections at multiple spatial and thematic resolutions, over a variety of geographic settings.

As with any modeling framework, there are limitations to the described framework. Currently, climate change effects are primarily handled from a top-down perspective. The IMAGE 2.2 model, used as input for the scenario construction, integrated the effects of climate change on modeled land-use proportions. From a bottom-up perspective, the spatial allocation component of FORE-SCE can dynamically update suitability surfaces for a given LULC type, based on projected climate data, allowing for patterns of suitability to shift as climate changes. However, climate effects on the suitability surfaces were small in most cases for this work, in part due to the thematic classification system that was used. For example, while suitability surfaces for individual agricultural crops such as corn or soybeans may show strong changes in response to projected climate change, the suitability surface for our aggregated cultivated crop class was much less affected. Increased temperatures and/or decreased precipitation may make a given parcel of land less suitable for corn, while soil conditions, topography, and other site-level conditions still may be favorable for cultivated crops that require less moisture, such as wheat. Without modeling individual crops, tree species, or other plant species, it becomes more difficult to model climate-induced shifts in geographic distribution of the aggregated vegetation classes mapped here. FORE-SCE also currently lacks the ability to model natural vegetation succession over time, including changes in natural vegetation communities in response to climate change or other natural disturbance.

Other disadvantages include the lack of an integrated hydrologic model, which influenced our ability to model changes in agricultural land in response to changes in water availability. Large swaths of agricultural land in the United States are dependent upon groundwater or surface water for the irrigation of crops. We did not have access to any regional- or national-scale hydrologic models to provide information on potential shifts in water availability under the different scenarios. In addition, we currently do not have a linked model to account for landscape disturbances due to fire, storm damage, or insect damage. Other potential disadvantages to the approach include an inability to track all sources of uncertainty in the modeling framework. As noted by Radeloff et al. (2012), land-use predictions over many decades are fraught with uncertainty, as we cannot predict socioeconomic and technological changes. For long-term projections such as these, the story-and-simulation approach that was used recognizes that statistical quantification of all sources of uncertainty is impossible. The scenarios provide likely landscape responses to a specifically defined set of driving force assumptions, with multiple scenarios used to more qualitatively bound uncertainty.

A formal validation of model results is also problematic for this application, with inconsistencies between historical data sources hindering a quantitative validation. FORE-SCE models the quantity of LULC change precisely, and quantity disagreement (compared to a reference source) is minimal. Comparisons with the 1992 and 2001 NLCD help identify issues with allocation disagreement, as do comparisons of scenario pairs, but a traditional, quantitative validation as is often performed for static LULC maps is still a challenge. Validation of stand age was also not a part of this study. Without explicitly modeling natural mortality, fire, and other events that may affect stand age, the absolute values of stand age as modeled are not directly comparable to a reference source for stand-age changes (as discussed in *Data availability and applications*). Even if we had modeled all processes affecting stand age, we lacked spatially explicit reference data.

Data availability and applications

Modeled data described in this paper are readily available through a USGS land-cover modeling website (*available online*).[9] Available data include annual LULC and stand-age maps for the historical period (1992–2005), and annual LULC maps and associated stand-age data for four different IPCC SRES scenarios for the projected period (2006–2100). Other data sets used in the modeling may be available for distribution by contacting the authors. The FORE-SCE model itself is not currently available for public distribution, but it is hoped that a distributable version of the model code will be available by late 2014.

Our four LULC projections represent the first national-scale, moderate resolution, thematically detailed LULC projections consistent with IPCC storylines that are available for the conterminous United States. The variability between the four scenarios captures much of the variability between other modeling frameworks (Table 5). Data and information on application of these data to address the biological carbon sequestration impacts of LULC change are *available online* from the USGS.[10] FORE-SCE spatial projections have been used in other applications to examine the impacts of LULC change on carbon and GHG fluxes (Zhao et al. 2009, Zhao et al. 2013). Viger et al. (2011) used FORE-SCE projections in the Flint River basin of Georgia to investigate the hydrologic effects of urbanization. The original FORE-SCE structure was designed to provide LULC input to the Colorado State University regional atmospheric modeling system (RAMS), a modeling framework capable of examining the impacts

[9] http://landcover-modeling.cr.usgs.gov
[10] http://www.usgs.gov/climate_landuse/land_carbon

of LULC change on regional weather and climate variability (Sohl et al. 2007). FORE-SCE LULC projections for the eastern United States have also been used to analyze changes in radiative forcing due to LULC-induced albedo change (Barnes et al. 2012).

The stand-age data were used to improve the modeling of forest change, but the data are themselves valuable for informing ecological applications. We modeled stand-age changes due to clear-cutting and land-use change, but natural mortality or death due to other disturbance factors (e.g., fire, storm damage, insect damage) were not considered. As such, the absolute values of stand age that are provided may be less valuable than relative changes in stand age over time. In many cases, the stand-age data can be considered intermediate proxy data that can be used to inform reconstructions of forest structure. Information on typical natural mortality ages for a region can be used to further enhance the stand-age data. Carbon modelers may use the stand-age data in association with regional forest inventory data to reconstruct likely standing biomass distributions. Weather modelers may use the stand-age data in conjunction with regional data on age and height relationships to develop surface roughness measures needed for weather and climate models. Wildlife modelers may use the stand-age data to reconstruct regional forest habitat characteristics.

The LULC maps are applicable to a variety of ecological applications (see Plate 1) that have a need for spatially explicit LULC projections. We are also currently working on backcasting LULC for historical periods, with historical LULC reconstructions back to 1938 being created for the conterminous United States. As the backcast data are produced, they are being made available online (see footnote 9). When the backcast work is complete, we will have consistent, annual LULC maps from 1938 through 2100, data sets that will facilitate the examination of past, present, and future LULC change and impacts on ecological processes.

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